Virtual Net Propagator: A Cloud-based Computational Tool for Systemic Decision Propagation Analysis

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ABSTRACT

Today's organizations are witnessing a growing complexity in making interconnected decisions. Where individuals have a wider range of decisions to influence, the consequence of decisions far more propagate across the system, and the business environment continually influences the status of the system. Predicting the cascading effects of decisions in such situations would be very problematic yet can have several implications for managers and executives to think beyond organizational silos and make local decision with a bigger picture of emergent consequences in mind. A prominent challenge within this realm is the ever-increasing complexity of decision propagations, especially when incorporating the role and influence of people involved in decision-making. This paper tackles this challenge from an engineering change perspective, with the focus on computing the compound risk of decisions when their consequences concurrently propagate across the system. We introduce an interactive tool called *Virtual Net Propagator*, which incorporates organizational dynamics into decision analysis, with the aim to identify change opportunities and effective set of interventions. Illustrated by a field engineering case study, it is demonstrated that the proposed tool can provide detailed knowledge on how decisions are interconnected and how systemic (cascading) effects of a decision propagate through causal pathways, so highlighting key influencers along with role and influence of interfacing (hidden) players.

Keywords: Change propagation; Complex networks; Computational intelligence; Systems design and analysis; Socio-technical systems; Web-based decision support system.

1. Introduction

Working in an ever-changing and hyper-connected business environment, modern-day managers are witnessing a growing complexity in making informed decisions. At the field operational level, the frequent changeovers in product (or service) functions make it difficult to gather experience on operations. At the organizational level, whilst decision-makers have typically a detailed awareness of their own part of the system, there is not often a direct link between decisions that are made in different parts (Hammond et al., 2002). The 'knock-on' effects of such decisions are becoming increasingly important and more difficult to predict across the system (Hassannezhad et al., 2021).

Therefore, predicting the desirability (or risk) of *decision propagation* is crucial for managers to think beyond organizational silos and make local decision with a bigger picture of *emergent* consequences in mind. However, such prediction would be particularly problematic in socio-technical context, where numerous interfaces between social and technical entities remarkably increase the degree of connectivity and there is not an explicit (measurable) knowledge on the role and influence of people involved in decision-making (Ullman, 2006).

This paper tackles this challenge from the perspective of *Engineering Change Management*, according to which 'effect' of a change in an interconnected system can be 'cause' for new changes (through their common interfaces) and so on, thus resulting into a propagation network with 'knock-on' effects (Koh et al., 2013). We discuss that despite substantial advancements in development of techniques to support change propagation (Hamraz et al., 2013), there is still lack of a 'reproducible' computer support that is capable of incorporating *organizational dynamics* into change propagation analysis. Such a tool must be able to deal with the algorithmic complexity of a *highly connected* socio-technical interfaces, whilst taking their amplifying, cyclical, simultaneous, and overlapping sphere of influences into consideration.

This paper introduces an innovative and interactive tool, called *Virtual Net Propagator* (http:www.virtualnetpro.com) – let us call it *Net Pro* in the rest of this paper. *Net Pro* offers a cloud-based business intelligence environment that allows the user to map out a system of interest, populate it as a probabilistic change model, and analyze its structural dynamics under various circumstances. It is developed in response to the needs of Telecom industry in understanding change priorities to improve complex business decisions and the gap in academia in developing tools that is callable of handling connectivity in studying change propagations, whilst based on the learnings and insights from the implementation of its predecessor *Decision Propagation Method* (*DPM*) – an excel-based research prototype (Hassannezhad et al., 2021).

Comparing to its former, *Net Pro* offers significant advancements in (1) *building* the model, by offering flexible dataset to be retrieved from existing models in the library, or being imported from an external csv-format file, or created from scratch; (2) *populating* the model, by allowing flexible change propagation steps, beyond three in DPM, initially set up to six; (3) *visualizing* the outcomes, by showing interactively how alternative system architecture leads to different sets of change patterns while offering better transparency on parallel causal pathways as well as 'hidden players'; and (4) optimizing the model, by allowing the user to apply concurrent change analysis and identify the largest impact in the system, thus identifying options that fit best with their strategic priorities.

Furthermore, *Net Pro* is developed in Python and empowered by Dash libraries to expand its utility as a data-driven web application. Such integration enables the tool to fit itself to the requirements of digital-age decision models, by providing accessibility over the cloud and compatibility to distributed business environments. The rest of paper is organized as follows. Section 2 discusses the background in Socio-technical complexity of decision modelling and analysis, followed by identifying the need for developing a new tool in section 3. Section 4 describes the structure and mechanics of the tool, which is demonstrated by a real engineering case study in section 5. The paper eventually concludes in Section 6.

2. Background

2.1. Socio-technical complexity of decision-making

The socio-technical aspect of decision-making goes beyond prediction of *what* will happen to the business under certain circumstances and places the emphasis on *how* the role and performance of people (involved in decision-making process) influence the desired set of outcomes. It is based on the premise that, even if people in an organization are not *directly* involved in decision-making (Fig. 1), the mechanisms by which they act and interact within the system can *indirectly* influence the technical outcomes of decisions (Hassannezhad, Cantamessa, et al., 2019).

Integration of such direct and indirect socio-technical influences into decision modelling would become more relevant in today's interconnected businesses as organizations are getting out of decision silos. Whilst there is not a direct link between the decisions that are made by different business units, in practice, the decisions taken in one unit may have consequences that relate to other units. Proactive understanding of decision connectivity can enable decision-makers to understand where to intervene in the system, and

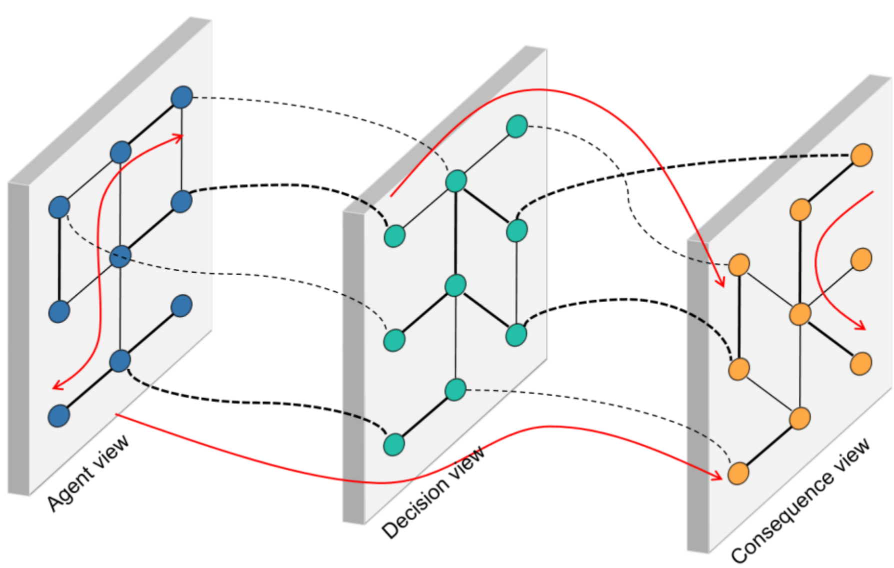

Fig. 1. Socio-technical aspect of decision modelling: people involved in decision-making (Agent-view) make decisions (Decision-view) which directly and (or) indirectly affect consequence outcomes (Consequence-view)

eventually, to direct unintended consequences towards something manageable where they have the control to either accept or mitigate it (De Smet et al., 2017).

The socio-technical view of decision-making can therefore be more *pragmatic* in the sense that it provides a more holistic and realistic representation of the reality (De Bruijn & Herder, 2009). Though, it can be more *problematic* as it adds to the complexity of the decision model, in terms of the number of variables (system components) and their links (causal pathways) to be modelled (Mumford, 2000), and the difficulty of providing explicit knowledge on these links. The next subsection discusses the challenge from a change modelling point of view.

2.2. Methods and tools supporting change propagation

Predicting the indirect ('knock-on') effects of change has long been used as a mechanism to inform early decisions in product design and development projects (Eckert et al., 2004). Numerous methods have been proposed in the research literature (for reviews, see Jarratt et al. (2011) and Hamraz et al. (2013)), using adjacency *matrix* and complex *network* properties to understand how change in upstream decisions (e.g., a new change request) affects downstream workflows, hence identifying factors that are more resilient or susceptible to change.

However, there are few examples that have been implemented in software programs and applied in real business settings, listed in Table 1, including CPM (Clarkson et al., 2004), DEPNET (Ouertani et al., 2007), ADVICE (Kocar & Akgunduz, 2010), ISF (Ahmad et al., 2013), and DPM (Hassannezhad et al., 2021). CPM, for example, uses the direct dependencies between component pairs and applies a numeric algorithm to calculate the combined risk of change propagation, where risk is defined as the product of likelihood and impact. The utility of the original algorithm, implemented in the CAM software (Wynn et al., 2010; Barzegar et al., 2018), has been improved by several subsequent studies. Hamraz et al. (2012) combine CPM with FBS and develop a linkage model to study the interdependencies between product forms and functions. Koh et al. (2013) add the 'reachability' factor to CPM to consider the decreasing ability to carry out changes as the change propagation path gets longer. Ahmad et al. (2013) improve the utility of CPM to consider multiple initiating changes and combine it with a graphical interface (called Information Structure Framework, ISF) to facilitate tracking a change from product requirements through to the process task.

Despite such capabilities, expanding the modelling scope to incorporate organizational dynamics and socio-technical interfaces poses substantial limitations to the existing body of literature (Table 1). First of all, a common criticism facing the majority of the methods (including the ones mentioned earlier) is that they are primarily developed for sparse technical problems, and dealing with the complexity of tightly connected socio-technical networks makes the model either fully saturated or too complicated to be manageable (Hassannezhad et al., 2021). Simplifying the reality, on the contrary, may become problematic, since an unimportant link might be a carrier of an important change across the network. Additionally, existing methods do not typically allow cyclical impact and feedback loops (Keller (2007); Lee & Hong (2017)) which is quite common in organizational settings. For example, the tree-like structure of CPM, with underlying 'brute-force' search algorithm for identifying propagation network, does not allow self-dependencies and cyclical paths.

Table 1. Comparison of few existing change propagation software tools against requirements of socio-technical modelling

	ADVICE [1]	CPM [2]	DEPNET [3]	ISF [4]	DPM
Socio-technical interfaces	-	-	-	-	Limited
Overlapping change effect	-	-	-	-	Limited
Cyclical change effect	-	-	Limited	-	Advanced
Flexible propagation length	Limited	Advanced	-	Advanced	Limited
Transparent paths and routes	-	Limited	Limited	Limited	Limited
Multiple visualization	Limited	Advanced	Limited	Advanced	Advanced
Multiple changes analysis	Limited	Advanced	Advanced	Advanced	Advanced
Trade-off analysis	-	-	-	-	-
Cloud-based access	-	-	-	-	-

[1] Active Distributed Virtual Change Environment

[2] Change Prediction Method

[3] product specification DEPendencies NETwork identification and qualification

[4] Information Structure Framework

Furthermore, existing methods have mostly been focused on identification of the riskiest components in the system and, despite few attempts (including DEPNET (Ouertani et al., 2007), ASF (Ahmad et al., 2013), and design workflow (Wynn et al., 2014)), very little attention has been given to dynamics of causal pathways; i.e., the way cross-functional teams interact and influence a decision. As such, the black-box nature of existing models may become an obstacle in generating actionable insights and transparent knowledge on the mechanism by which changes propagate between the initiating and influenced pair of components.

The previous work undertaken by the first author and his colleagues tackled the above discussed challenges by development of the Decision Propagation Method (DPM) (Hassannezhad, Cassidy, et al., 2019). The method, implemented in an Excel-based prototype, places the emphasis on the algorithmic complexity of a complex socio-technical system (fully connected) and presents a systematic aggregation algorithm to quantify the risk of change propagation, by allowing all types of couplings (such as direct, indirect, and cyclical) within a network and taking their amplifying, concurrent, and overlapping effects into computation.

2.3. The need for development of a new tool

The primary application of DPM in real industry settings, reported in Hassannezhad, Cassidy, et al. (2019) and Hassannezhad, Cassidy, et al. (2021), necessitated the need for development of a novel software prototype that is 'scalable' to support any size of complex business problems, is 'reproducible' to adopt updated information and learn from data in real time as new data emerge (e.g., refining strategies or new change requests), while providing detailed knowledge about propagation pathways, without too much technical knowledge required from the user (i.e., decision analyst, domain experts). Such a tool should ideally be 'flexible' enough to be applied beyond specific engineering applications, such as in hyper-connected policy systems. In particular, the initial implementation of DPM tool revealed a number of limitations pertaining to:

- **Model building**: there is a fundamental assumption in DPM about flow of decision propagation in a system based on which, an organization can be seen as a three-layer network in that people (called agents in the model, see Fig. 1) make decisions and decisions influence consequences (known as objectives) which in turn affect the performance of people. As a result, there is no direct link between decision variables in the network and no feedback link from consequences to decisions – this is only viable through agents. Whilst we found this assumption valid at the organizational strategic level in this specific case study, it might not always be the case; for example, business problems at the operational level are more concerned with investigating the interplay between decisions. Furthermore, data model in DPM is a built-in function, whereas many real-world decision problems may require accessibility across platforms, for example, through importing data from an external source.
- **Model population**: DPM is primarily designed for analyzing propagation in multi-layer network, yet the computation of combined risk in the original tool is confined to up to three propagation steps. Whilst this may be interesting enough to make the outputs non-trivial, it does not use the information of the entire network, and so there is a risk of losing important (indirect) pathways across layers. This limitation would be particularly important when modelling large complex systems with more than three layers, where three propagation steps cannot explicitly determine manifold causal pathways between initiating and influenced components.
- **Model visualization**: The DPM dashboard mainly relies on a scatter plot to visualize the compound risk between components, and the static Sankey diagram only shows the high-level routes from agents to consequences. As a result, there is very little information provided on underlying propagation pathways between two parts of the system, perhaps due to inherent limitation in MS Excel for incorporating interactive network view. Such information would be particularly important to identify those 'hidden' players by which a change propagates across the system.
- **Model analysis**: An essential part of a change modelling tool is enabling the user to proactively evaluate alternative business conditions in order to identify potential change opportunities. In DPM, similar to CPM, due to their matrix nature, the user has to go back to the input data model and search for the corresponding box in the multi-layer matrix to make a change; this would be problematic in large scale systems with numerous connections and potentially an error-prone process, and would not be straightforward to apply more than few changes.

Consequently, the present study aims to overcome such limitations by introducing a novel software tool. The next section describes the proposed *Net Pro* tool in details.

3. The proposed Virtual Net Propagator tool

Net Pro is an interactive decision support tool aiming to provide managers better control over decisions that are being made. The essence of such a control mechanism is based on predicting the propagation risk of decision consequences (across the whole system); this proactive approach is broadly referred to *value-focused* thinking as opposed to reactive *alternative-focused* thinking in the literature of decision science (Keeney RL, 1994).

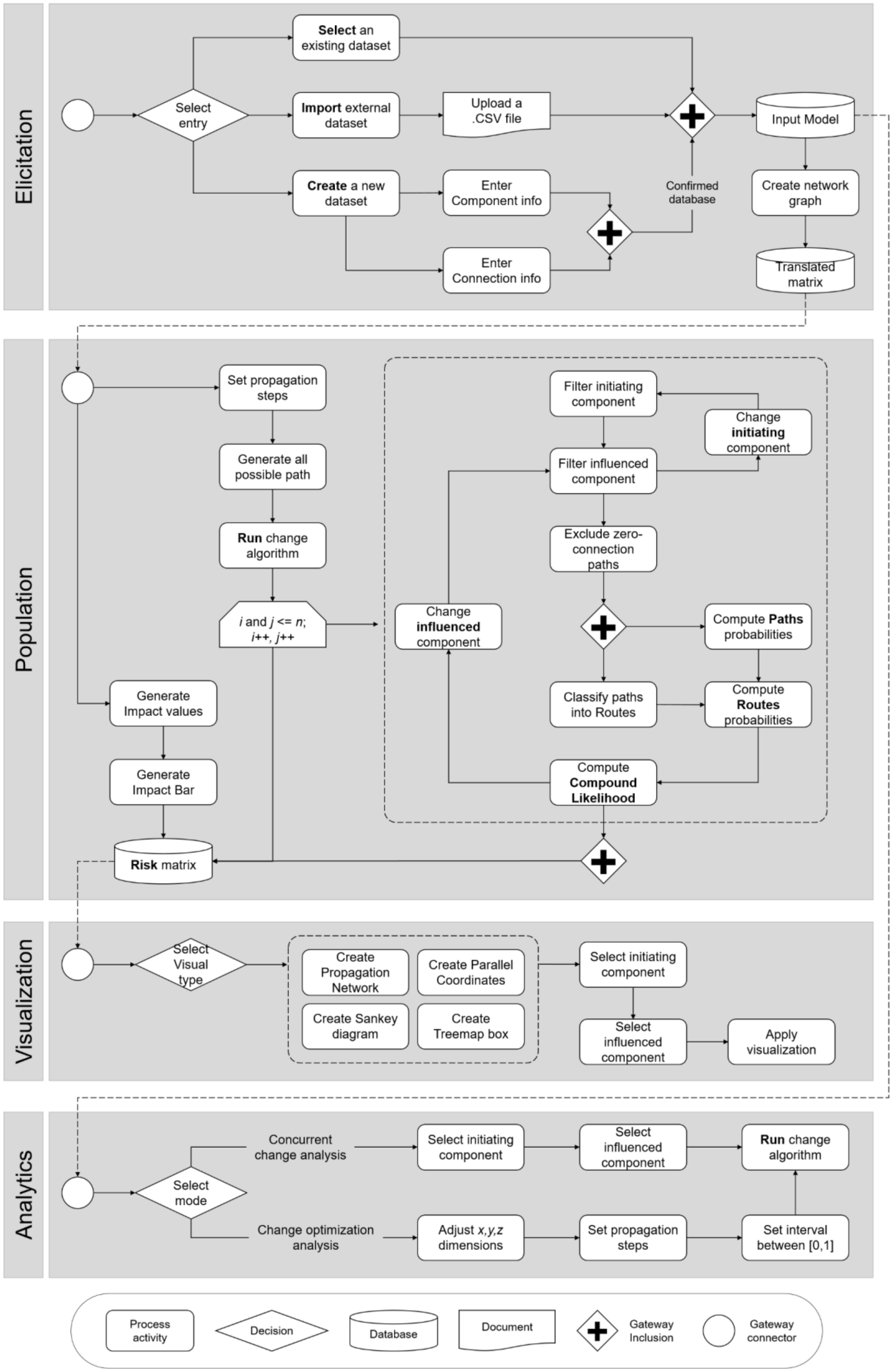

Fig. 2. The flowchart of the *Virtual Net Propagator* algorithm

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Net Pro provides a dynamic integrated platform for designing a ‘perceived’ system (based on the knowledge of domain experts) and evaluating its structural dynamics in different business settings. A crucial part of this is showing interactively how alternative system architecture leads to different sets of outcomes, thus allowing decision-makers to identify effective interventions, i.e., options that fit best with their strategic priorities. This can have numerous applications in today’s complex connected systems (e.g., design concept selection, policy options analysis) where business ‘success’ requires well-aligned decisions (or strategies) across different units, whereas each unit has its own priorities which may be seen as contradictory to other units, and the system is continually affected by exogenous circumstances.

The core of *Net Pro* is computing the systemic effect (by including both direct and indirect impact) between any component pairs in the system, in the form of compound risk. The presumption is that change in the system propagates via connections, and the strength of a connection can determine the proportional likelihood of a change between adjacent neighbors (Hassannezhad, Cassidy, et al., 2019). *Net Pro* applies the *Path Searching* (refers also to A*) algorithm for this purpose – as opposed to *Brute-Force* search in CPM (Clarkson et al., 2004) – to build a tree of all possible paths originating from the initiating node and extending to the targeted (influenced) node. This will eventually provide a better transparency not only on key causal pathways across the system, but also relating to those critical interfacing components (referring to ‘hidden players’ in this paper) between the two ends (Fig. 7).

Net Pro offers an extensive data elicitation, visualization, and analysis platform to support implementation of the tool in different settings. Technically, the tool is written in *Python* programing language and combined with the *Dash* framework to expand its utility as a data-driven web application. It can be implemented either locally using an executable file (only available for Microsoft Windows, at this initial version) or through a Web Server to be accessible over the Cloud – without the user having to code. Structurally, as illustrated by a flowchart in Fig. 2, *Net Pro* is composed of four work packages which are manifested respectively as data elicitation, population, visualization, and analytics tabs in the tool’s user interface (Fig. 3) and described in the following sections.

3.1. Data elicitation tab

The input to *Net Pro* is a causal-and-effect diagram; in particular, a fuzzy cognitive map (Papageorgiou & Salmeron, 2013). It is a signed fuzzy weighted digraph composed of nodes (indicating system components) and edges (indicating cause-effect relationships among them). The weights of the edges show the strength of causal influence between nodes, typically assigned by experts either linguistically (e.g., in form of Weak, Moderate, and Strong link) or as probabilistic values bounded within range of [0,1]. Its simple architecture makes the model relatively quicker and easier to parametrize from a varied source of qualitative knowledge, which is understandable by non-technical audience (without prior knowledge of computational modelling), and suitable for applying to poor-data and multi-interest situations. There are three ways to create an input model in *Net Pro* (Fig. 3A):

1. **Retrieving** the dataset amongst existing stored models in the tool library – typically the case for a deeper investigation of models that are already being mapped;

2. **Importing** a dataset from a local or cloud-based csv-format file, e.g., using in conjunction with another diagramming or systems modelling tool; and,
3. **Creating** a new dataset from scratch, thus acting as an integrated systems modelling and analysis tool – the created model can be exported to an Excel file or stored in the library for further use.

Central to this process is transforming the input (e.g., fuzzy cognitive map) model into an adjacency (square) change matrix model, in that columns represent the initiating component and rows represent the influenced ones – when a change request receives, and the value of matrix indicates the strength of direct links between system components in the form of (translated) probabilistic values. In the default format, analogous to DPM, there are three layers in the matrix respectively representing the individuals involved in decision-making (*Agent* layer), variables that drive system performance (*Decision* layer), and the outcomes of decisions in the form of objective, consequence, or action (*Consequence* layer) (Fig. 3C). However, unlike DPM bounding to 40 components in the model (as maximum coverage), there is no limitation on the size of a business problem in *Net Pro*. Accordingly, if the decision problem does not encounter for example the influence of individuals in the model, the corresponding layer can be excluded from the computation by assigning Zero to the number of components field.

Apart from flexibility in creating an input model, the power of data elicitation in *Net Pro* lies in its adaptability in capturing changes to the input model, e.g., as data evolve over time or new data emerge. Basically, the input causal-effect model represents a static version of the system at a given time, which is highly subject to changes over time. This can be performed either by updating and uploading the external csv-

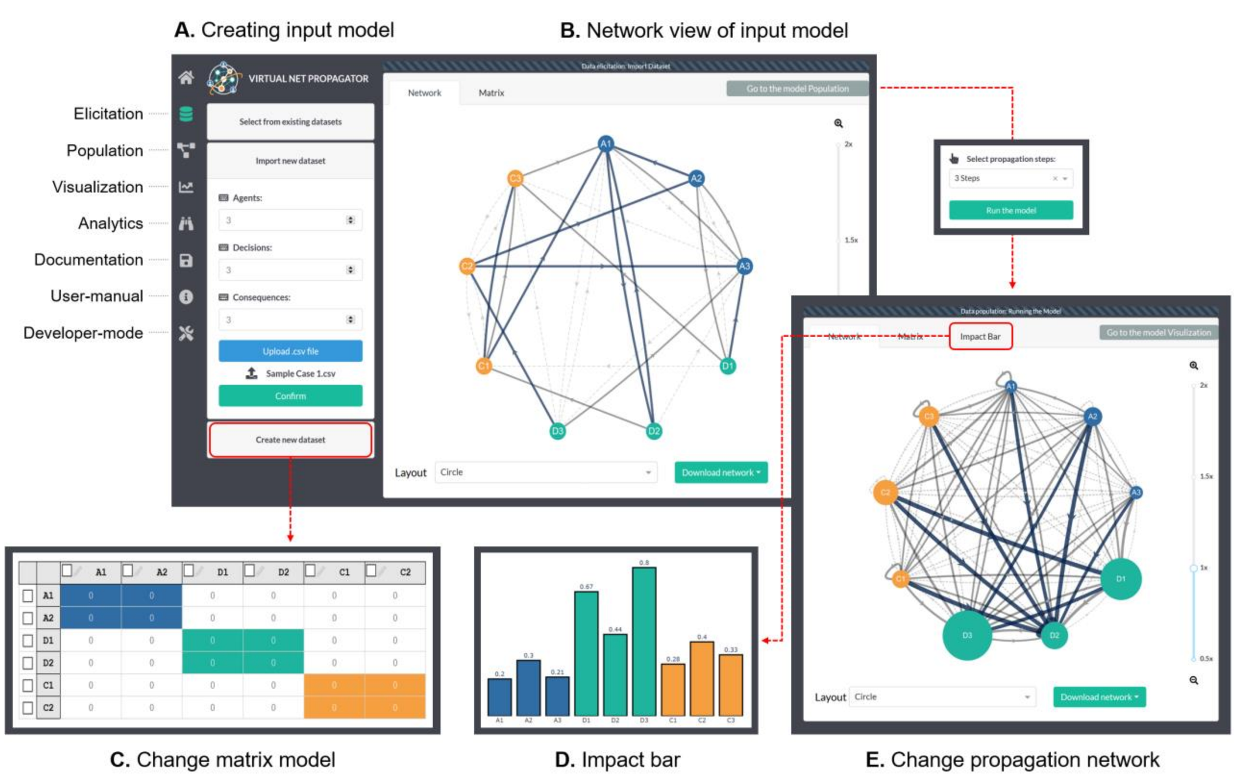


Fig. 3. Overview of the *Virtual Net Propagator* interface: Data elicitation (A-C) and Population (D-E) tabs

format file (in import mode) or by manually changing the structure of model (both components and their links) in the input matrix (in create mode). Furthermore, if the goal is applying change propagation analysis to a specific class of data in the input model, and not the entire system, then user can exclude the surplus data by simply unchecking the corresponding columns for *neutralizing* the component (removing the influence of a component from the whole system) or row for *freezing* the component (removing the influence of system on a particular component) in the matrix mode. By confirming the database, the network view of the model (Fig. 3B) shows the system architecture before applying the change propagation algorithm.

3.2. Data population tab

Data population turns the causal-effect network (only representing direct impacts) into a change propagation (risk) network (also considering indirect propagation of direct impacts). Instrumental to this computational process is the DPM multi-level aggregation method (Hassannezhad et al., 2021); it computes the compound risk between any component pair in the network. In DPM, the Compound Risk (CR_{ab}) of a change between initiating component (a) and affected component (b) is the product of Compound Likelihood and Impact. Compound likelihood (CL_{ab}) measures the probability that change in an instigating component (a) will lead to change in a nonadjacent component (b), and is computed through the following three-step process – a full description of the computation method with an example is illustrated in Hassannezhad, Cassidy, et al. (2021):

1. *Component-level aggregation*: to compute probability of direct links between common interfaces in a single path, using the union AND ($\cup$) operator;
2. *Route-level aggregation*: to compute multiple propagation paths in a single route, considering their overlapping impact; and,
3. *Network-level aggregation*: to compute multiple routes in the network.

The computed CL_{ab} will then be multiplied by Impact of the initiating component (I_a) to obtain the resultant value of CR_{ab}. Impact (I_a) is a ratio that approximates the tendency of component (a) in propagating changes to the other components. It is based on the measure of Criticality (Cr) which is defined as the fraction of the cumulative strength of outgoing links (columns in the input matrix) over incoming links (rows in the input matrix). Therefore, the higher value of impact determines more *activity* in terms of influencing the rest of system while lower value shows more *passivity*, meaning to be more affected by the system.

Running the computational model requires the user to set the number of *propagation steps*. It determines how far a change can be propagated across the system. In the original DPM tool, the length of propagation was confined to three, and has been expanded in *Net Pro* to cover a range between two and six, thus ensuring that all causal pathways between a component pair are considered in the computation. The experiment of using different propagation steps in this study shows that propagation of a change more than four steps does not usually make a sensible impact on the outcome (Fig. 4, top), reaffirming the existing evidence in the literature such as studies reported by Eckert et al. (2004) and Pasqual & De Weck (2012).

Understanding a reasonable number of propagations is very important, particularly for complex connected networks, as increasing the propagation steps exponentially increases the computational complexity of the model such as data processing time (Fig. 4, bottom). The figure shows that, depending on the complexity

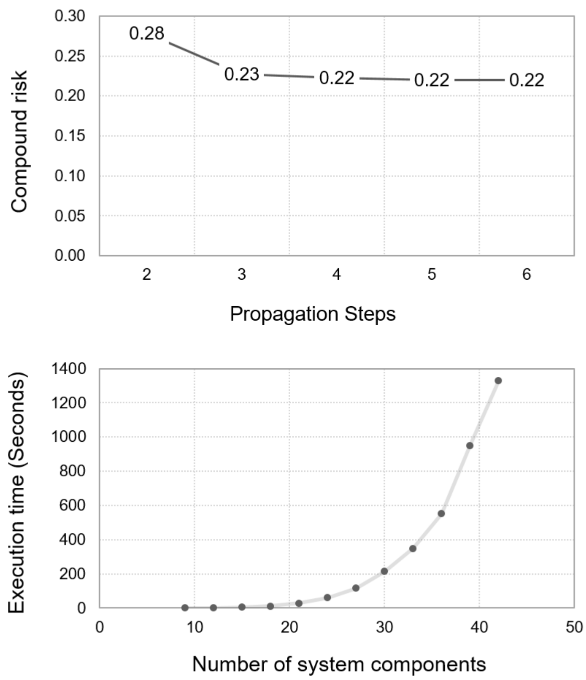


Fig. 4. Impact of propagation steps (top) and size of the system (bottom) on increasing the computational complexity

of the problem, it may take from minutes to hours of processing time to get the outcome propagation network, during which the algorithm repeats the above process for all initiating components (column headings) and affected ones (row headings) to obtain the corresponding values of Compound Likelihood and Compound Risk (for all links), and the impact (for all components) – see the population workflow in the flowchart in Fig. 2. It can be shown that the expected number of propagation paths $E[p]$ being computed for a system with n components and a density of d (defined as the number of existing links divided by the number of possible links) grows exponentially with the number of components (Keller, 2007), represented by below formula:

$$E[p] = n \sum_{i=1}^{n-1} d^i \frac{(n-1)!}{(n-i-1)!}$$

The resultant data is then presented in form of propagation network, similar to what is shown in Fig. 3(E), in that thickness of links represents the compound risk between connected components, and size of nodes indicates the impact of corresponding component, also presented in form of bar chart (Fig. 3D). The propagation network alone can provide some insights on identifying key system drivers and the key causal pathways amongst them. However, a more detailed investigation of causal pathways (and underlying 'hidden players') can be obtained through the data visualization tab.

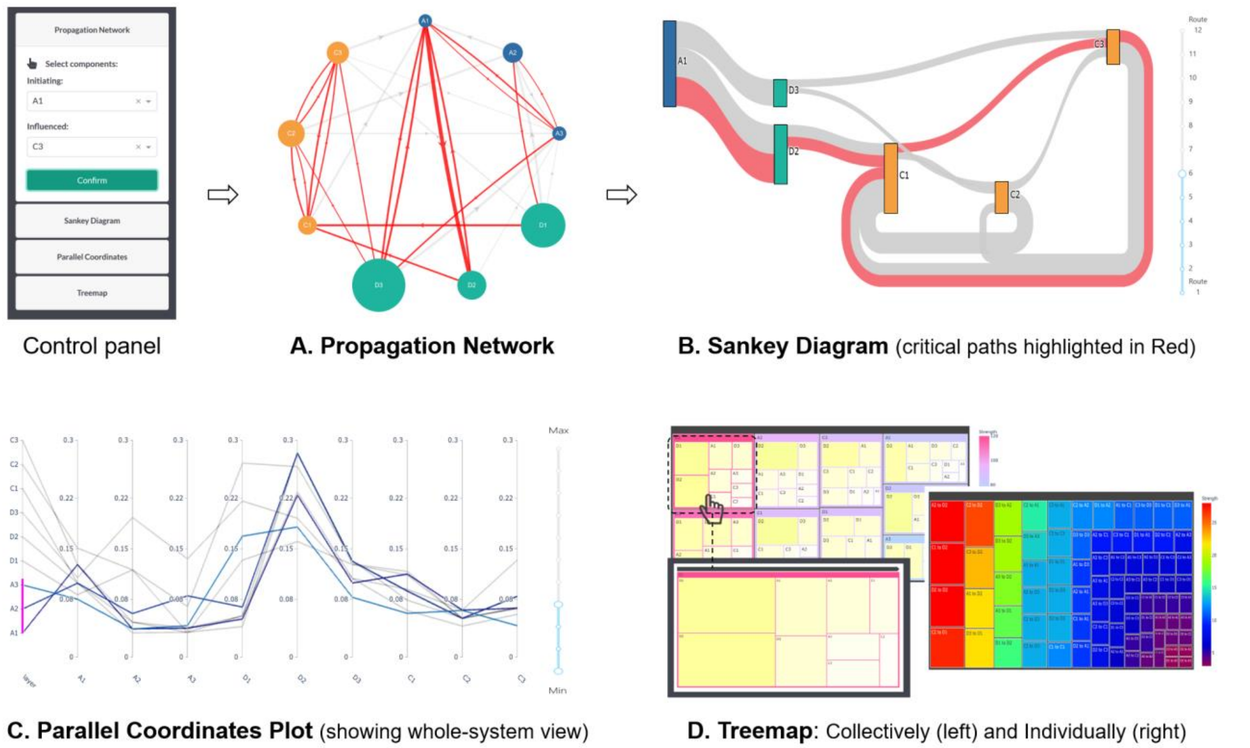


Fig. 5. Diversity of visualization tools (modelling views) embedded in *Virtual Net Propagator*

3.3. Data visualization tab

The data visualization tab provides an interactive visual interface to help decision makers in *analytical reasoning*, by allowing them to encapsulate complex information, comprehend the relationships, manipulate the data, and identify places in the systems to intervene. *Net Pro* is equipped with an extensive range of data visualization tools (Fig. 5), thereby decision makers can run a deep dive investigation on propagation paths and routes reside in the network. They include:

- **Network map** illustrates all possible paths and routes between a pair of initiating and affected components in the network, selected by the user from the dropdown boxes (Control Panel in Fig 5). This function would be useful in *exploring multiple types of couplings* (such as direct, indirect, or cyclic) between selected components and how this customized network places within the bigger scale of the whole system, in terms of including critical pathways. Accordingly, hovering over any of these components or connections provides further information in terms of the value of compound risk (clicking on components) and impact (clicking on components) (Fig. 5A).
- **Sankey diagram** provides a deeper dive into the causal pathways and demonstrates all possible routes between the user-selected pair of components, thus uncovering the interfacing component

(components that are carrier of influence (change) and located between the source and sink components) and their interconnectivity. It reveals for example multiple possible ways that an agent can influence a decision outcome, e.g., through D_2, D_3, C_1, and C_2 in Fig. 5(B). In complex systems, where there is often no direct link between the decisions that are made within different system parts, this sort of *whole-system understanding of causal pathways* can provide important insights on how decisions are interconnected. The width of arrows (links) in the Sankey diagram is proportional to the compound risk (CR), and the critical pathways within each route are highlighted in red, with the right sidebar enabling the user to switch between multiple routes between components (far right in Fig. 5B).

- **Parallel coordinates plot** provides a multi-dimensional view of the amount of CR in the user-selected layers, e.g., showing (whole-system) parallel influence of agents, decisions, and their consequences, where each polyline in the plot corresponds to a system component (e.g., an agent) and each parallel axis can be customized to indicate, for example, a consequence (Fig. 5C). The parallel coordinates plot helps identify *where a system driver produces the largest effects* on priority consequences. In addition, it allows the user to determine trade-offs emerging between different outcomes (Consequence-Consequence plot) and advising on what settings should be made at the decision layer (Decision-Consequence plot) and agent layer (Agent-Consequence) to achieve these trade-offs.
- **Treemap box** provides a systematic visual method for *hierarchical representation of data*, that is by ranking them from the riskiest link (top-left) to least risky one (bottom-right) based on their value of compound risk (Fig. 5D). This enables the user to drill down within the data to identify the most (or least) critical pathways in the system at a glance. There are two options in doing so: looking at the whole-system link data (where each box in Fig. 5D (right) is corresponding to a link) or narrowing down the scope to hierarchically show the mutual links for a specific-component (Fig. 5D, left).

3.4. Data analytics tab

The visualization tab demonstrates the structural dynamics of the system at a given time. While it cannot reflect temporal and spatial dynamics, the semi-quantitative representation of cause-effect relationships in the input model allows the user to simulate 'what-if' scenarios to proactively evaluate alternative conditions and identify potential opportunities for change to improve outcomes. In this sense, *Net Pro* acts as a dynamic modelling tool whose further iterations can eventually provide a better resolution of system structure. The data analytics tab offers two original functions to help with this process:

Concurrent change analysis provides an unlimited and interactive capacity to change the structure of system (e.g., adding or removing links from the input model, or changing the strength and directionality of links) and rerun the change propagation algorithm to see where the *largest systemic effects* on the system are (either positively or negatively). It can be used to understand the impact of different policy options, for example, what decisions (or outcomes) might be most affected if we take the full responsibility of a decision from an individual and share it amongst the team. By selecting any pair of (initiating and influenced) components from the left sidebar, the user can check if there is a direct link between them (Fig. 9A) and adjust it to an intended setting using *drag-and-drop* (Fig. 9B). By confirming all desired changes, it takes up to a few minutes (for large-scale problems) for the spark bar chart come up, providing a simple and uncluttered view of rises and falls in the compound risk of other system links, with an option to customize the visualization to any of the agent, decision, and consequence layers.

Change optimization analysis offers an interactive tradeoff space to investigate the relationships within a large multivariable system architecture to identify feasible alternatives that satisfy the desired outcome, through understanding the sensitivity that a specific link in the system shows with respect to changes in two other links – in terms of compound risk. For example, understanding how various degrees of connectivity between the director and deploying engineers (A_1D_2) and controller and quantity of performing tasks (A_3D_3) affect the influence of planner over total cost (A_2C_4) (Fig. 10). In addition to two variables (X-axis and Y-axis) and the objective function (Z-axis), the user needs to set up the number of intervals and propagation steps. For example, if the interval is set to 10, the optimization model breaks the range of strength values [0,1] into 10 pieces for each dimension, then starts with a minimal value of zero, operates the propagation algorithm, records the values of corresponding axes, adds 0.1 to the input data (for only one of the dimensions), and repeats the process until all three dimensions reach the upper threshold of 1. In this case, the total number of simulation runs would be equal to 1000 ($Intervals^3$). The shape of the output plot (a kind of heatmap) then determines if there is synergy (or conflict) emerging between the dimensions and where to get the *most effective trade-off*, satisfying the objective function.

4. Software implementation to a real-world engineering case

This section demonstrates application of the proposed software tool to a real engineering problem. The presenting results can be a starting point for many deeper analyses to understand, interrogate, and control risk of change propagation towards identifying potential change opportunities. However, the focus of this paper is the prototype tool, in particular stipulating its performance in addressing industry and research needs, and the case study has been presented here to prove its applicability to an 'introductory' case of British Telecommunication (BT) Field Engineering division. Therefore, a further discussion of the results and presentation of possible analyses go beyond the scope of this paper; the interested reader is referred to Hassannezhad, Cassidy, et al. (2021) and Hassannezhad, Cassidy, et al. (2019).

4.1. Field engineering case study

BT's field engineering division is responsible for the forecasting, planning, and allocation of tasks for a network of nearly 25000 field engineers across the UK so as to enhance the quality of service and meet customer commitments while moderating the operations cost. The process involves numerous stakeholders (such as employees, contractors, and customers) whose performance and behavior (e.g., interaction with each other and with forecasting tools and equipment) would not be the same on any two consecutive days. The objective of this case study is to improve business agility in responding to changes through predicting what might possibly go wrong in the process, and how unplanned changes affect the performance of other roles and the emergent system behavior.

The primary field engineering system model has already been developed through a participatory process (led by the first author and involving multiple domain experts) to understand the cause-and-effect network

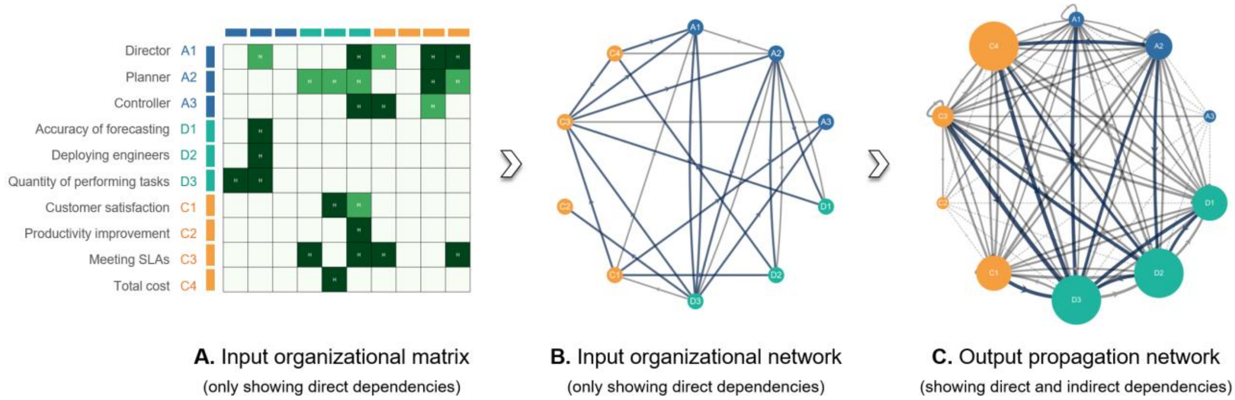


Fig. 6. Structure of the BT's field engineering system: before applying propagation algorithm (A-B) and after that (C)

(Hassannezhad, Cassidy, et al., 2019). The study generated knowledge about the field engineering system structure, in particular its divers (21 components: five agents, six decisions and ten consequences), 420 links between them (164 Strong, 131 Moderate, and 125 Weak links), and change propagation risk analysis based on that structure (Hassannezhad et al., 2021). The reduced version of this generated model, based on three agents, three decisions, four consequences, and 25 links (shown in Fig. 6A), has been used in this study as the input dataset to illustrate the implementation and credibility of the proposed tool against requirements that identified earlier in Sec. 2.3.

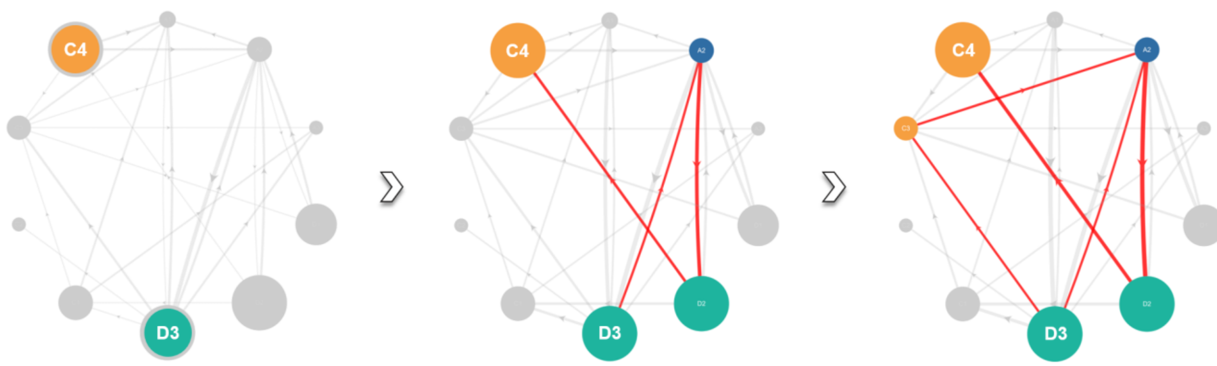
4.2. Implementation results and discussion

To implement the *Net Pro*, the input model was uploaded to the data elicitation tab (in the form of an adjacency matrix) and run by the population tab using *four* propagation steps; it was the suggested choice by previous studies (discussed earlier in Sec. 3.2), while coping with the limitation of original DPM tool in handling more than three steps. Fig. 6 shows the network architecture of the system before taking the indirect dependencies into computation (Fig. 6B) and after that, showing the outcome propagation network (Fig. 6C).

The size of nodes in the propagation network represents the impact of system components (which is defined as the tendency of a component in influencing the system), indicating D_2 (deploying engineers), D_3 (quantity of performing tasks), and C_4 (total cost) as the most influential components. The color-coding and thickness of links in the network map can determine the riskiest relationships (with detailed information provided in Treemap), such as the cyclical effect of 'quantity of performing tasks' (D_3); from the propagation network at the visualization tab, it can be shown that there are 15 unique pathways through which a change in D_3 will lead to a cyclical effect.

4.2.1. Understanding hidden influences

Further investigation of propagation network can uncover important information about how two components that are not directly linked can influence each other through manifold indirect connections. An



A. Second-order propagation
(link from D_3 to C_4 is not existed)

B. Third-order propagation
(D_3 - C_4 exists via A_2 and D_2)

C. Forth-order propagation
(D_3 - C_4 exists via A_2, D_2, and C_3)

Fig. 7. Understanding 'hidden' (indirect) influences in the system: the role of high-order propagation

example would be the interplay between the two most influential components in this case study. Despite no direct link from $D_3 \rightarrow C_4$ in the input model (Fig. 6B), our experiments reveal a significant influence between them after two propagation steps (Fig. 7). This indirect influence is existed through two unique pathways: $D_3 \rightarrow A_2 \rightarrow D_2 \rightarrow C_4$ with three propagation steps (Fig. 7B) and $D_3 \rightarrow C_3 \rightarrow A_2 \rightarrow D_2 \rightarrow C_4$ with four propagation steps (Fig. 7C); in this case, A_2 (planner), D_2 (deploying engineers), and C_3 (meeting SLAs) are called 'hidden (interfacing) players'.

Such information can be used by decision-makers to understand not only what the likely effect of a decision option across the system is, but also how the underlying interplay between system components can affect the target outcome.

4.2.2. Understanding critical routes and paths

The information about mutual risks in the parallel coordinates plot shows that, despite no direct link, one of the largest influences amongst decisions is the effect of deploying engineers on quantity of performing tasks ($D_2 \rightarrow D_3$); it can be shown via the Sankey diagram that this combined effect is the resultant of aggregation of six unique routes (Fig. 8). In total, these routes contain 14 unique paths, half of which are identified as critical and highlighted in red in Fig. 8 within each route. In particular, the study of such propagation routes (and underlying pathways) can expose two main classes of information:

- Firstly, tracking the compound risk between a pair of component, $CR_{D_2 D_3}$ in Fig. 8(A), to the underlying routes and paths provides explicit information on *how a change propagates via interfacing components*. In the given example in Fig. 8(B), the interdependency from $A_2 \rightarrow A_1$ is instrumental in making routes $[R_4]$ and $[R_5]$ feasible. Fig. 8(B) also signifies that the strongest influence from $D_2 \rightarrow D_3$ is a kind of feedback loop, occurring when the consequences of decision D_2 affect involving agents A_1 and A_2.

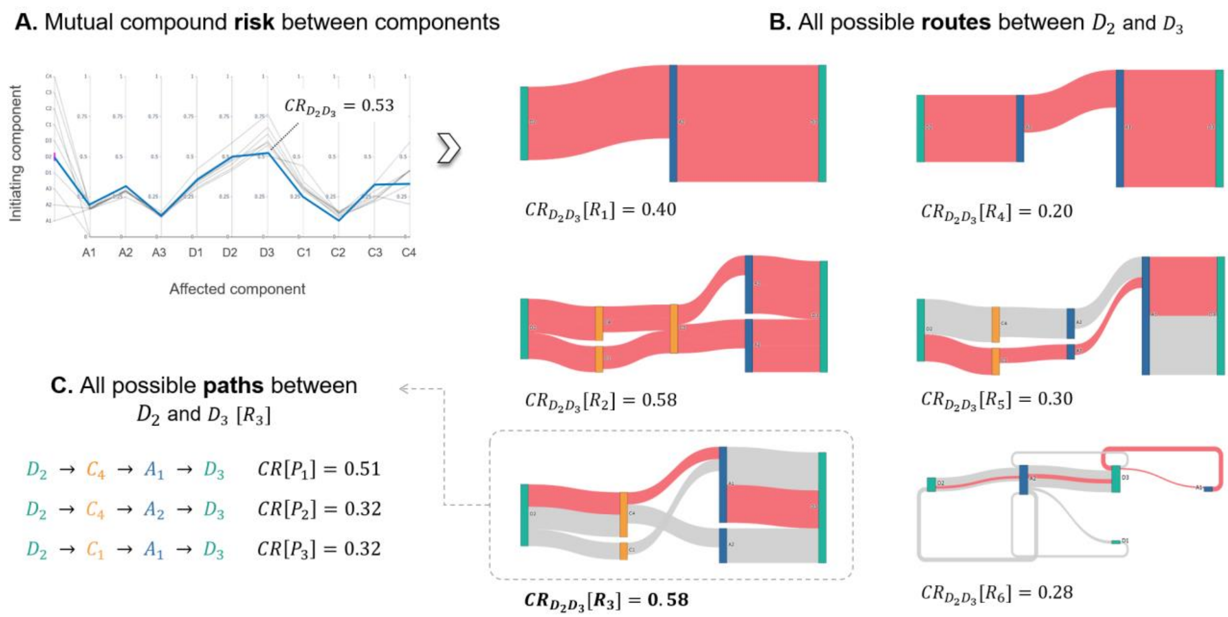


Fig. 8. Understanding the (hidden) players between Deploying engineers (D_2) and Quantity of performing tasks (D_3)

- Secondly, it determines *how an unimportant link might be a carrier of an important change*. For example, whilst the overall influence of customer satisfaction on director's decision $(C_1 \rightarrow A_1)$ is generally low in our case, such feedback information would be an integral part of the influence of director over quantity of performing tasks $(A_1 \rightarrow D_3)$, as per shown in Fig. 8 $[R_3]$.

4.2.3. Understanding effective interventions

A possible intervention in this case study would be giving the controller (A_3) the full responsibility on quantity of performing tasks (D_3) and taking it from others; currently, the controller has no influence over any of decisions. The scenario is simulated using the functionality of concurrent changes analysis in the data analytics tab, with the results demonstrated in Fig. 9. At first glance, the agent view interestingly shows a general fall in the influence of controller in the system while director (A_1) gains more power over other agents and the quantity of performing tasks (D_3). As such, it might be a sign of tension between the team over quantity of performing tasks (D_3), because solely giving the controller (A_3) the full responsibility to make a decision (D_3) does not necessarily mean translating it down through the organization unless other roles are given the responsibility to enact.

At the same time, D_3 clearly becomes more important, with the largest increase belonging to the influence of accuracy of forecasting, meeting SLAs, and total cost over quantity of performing tasks – shown as $D_1 \rightarrow D_3$ (in decision view) and $C_3 \rightarrow D_3$ and $C_4 \rightarrow D_3$ (in consequence view) respectively. It may imply that the business is coping with lack of accuracy of forecasting (D_1) with more workforce responses. Such understanding can allow policy makers to develop and test proposals in order to see where their decisions may have potential unforeseen outcomes.

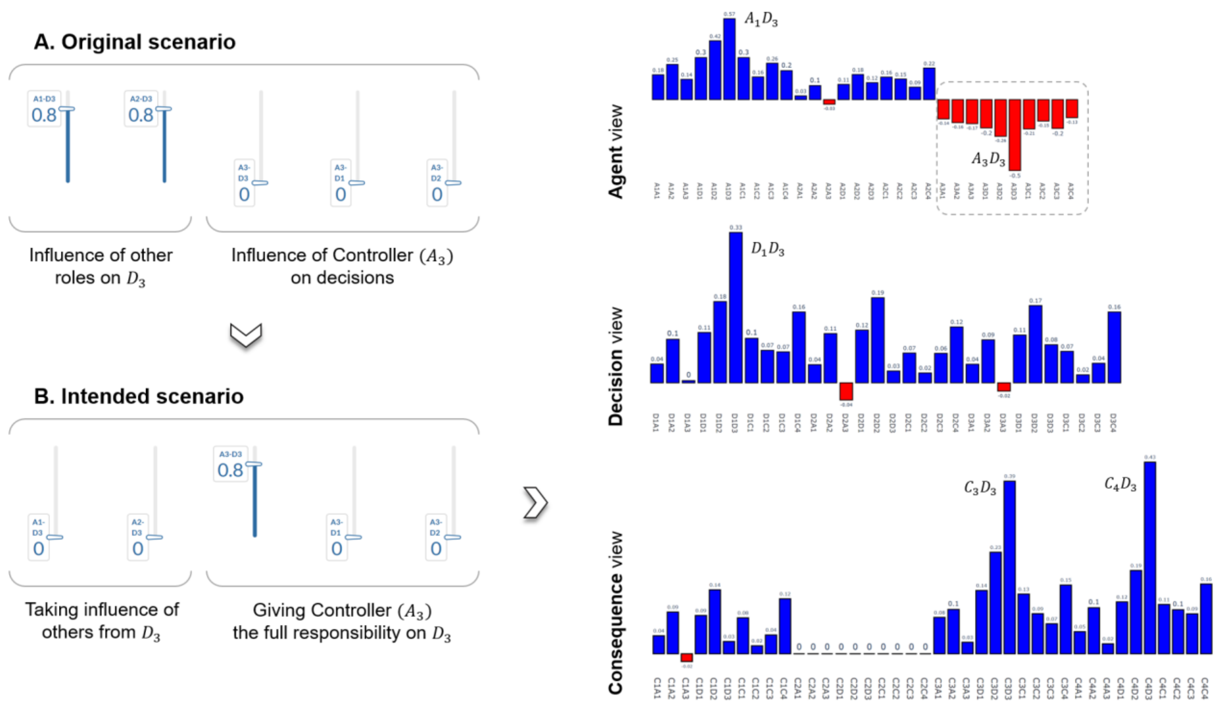


Fig. 9. Identifying effective interventions using Concurrent Change Analysis function

4.2.4. Understanding effective trade-off

The sensitivity analysis discussed earlier takes a forward approach to understand dynamics of the system under alternative circumstances, where we purposefully change the structure of system to reflect the intended situation and investigate how these changes affect the emergent system behavior. The optimization analysis panel complements this approach by running backward analysis, trying to understand what settings in the structure of system give us the desired outcome in the target link – between which there may or may not be a direct link. The trial question here, based on the earlier findings so far, is how structural dynamics (in form of various degrees of connectivity) between the director and deploying engineers (A_1D_2) and controller and quantity of performing tasks (A_3D_3) affect the influence of planner over total cost (A_2C_4).

In response, ten evenly spaced numbers over the interval of $[0, 1]$ were generated; then the model was run 1000 times (10^3) based on four propagation steps, and the value of compound risk corresponding to A_2C_4 recorded, as is displayed in Fig. 10 (A). The results indicate that the decision about deploying engineers by director (A_1D_2) has a higher influence over the target link between planner and total cost (A_2C_4) and the highest impact is achieved when the strength of A_1D_2 is above 'moderate' or there is no link between them; however, this correlation appears to be insensitive of the decision about quantity of performing tasks by controller (A_3D_3). A possible decision option might be improving the link between planner and controller (A_2A_3); the mutual sensitivity between $A_2 \leftrightarrow A_3$ seems to have a positive effect on both A_2C_4 and A_3D_3, as per respectively shown in Fig. 10 (B and C).

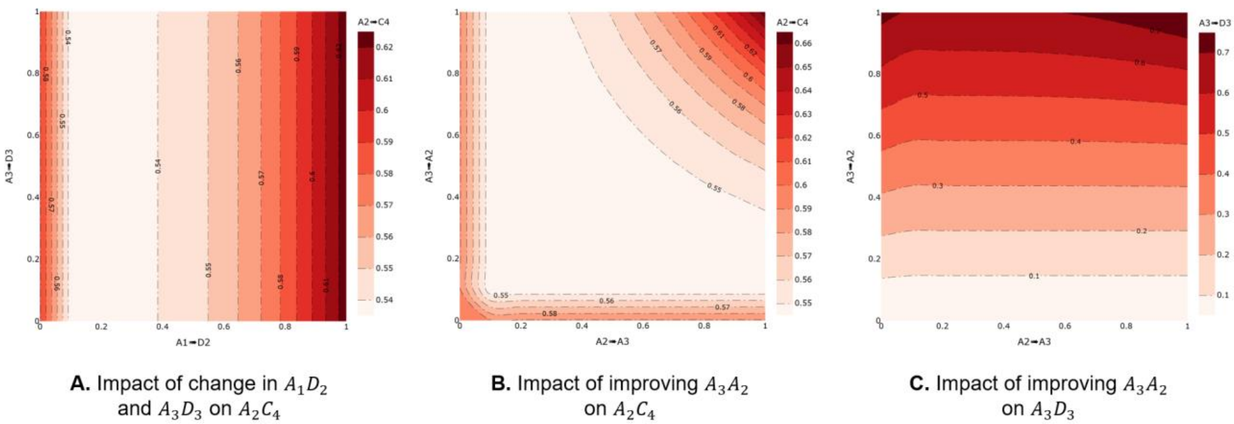


Fig. 10. Making effective trade-off using Change Optimization analysis function

4.3. Discussion

In this section, we used a preliminary case to demonstrate the applicability of the proposed tool. By taking a holistic view, we demonstrated how different roles involved in decision-making can directly and indirectly affect the decisions of other roles and the emerging consequences. Placing the emphasis on causal pathways across the system revealed that making informed decision in business environments involves more than identifying the expected utility (or risk) of decision options and without considering the interaction between organizational networks and technical business outcomes, the decision model tends to underperform in real settings.

Net Pro is primarily designed for early stages of business process where the problem is messy or unclear and decisions have significant impact on downstream workflows. This may have positive implications for dealing with information uncertainty (e.g., imprecise, and implicit data) but at the same time, it does not consider the actual values of the components and explicit nature of the links. Therefore, it cannot make quantitative predictions; it rather shows what will happen to the system under given conditions of relationships. Furthermore, the initial version of the tool presented in this paper is limited to three layers which may confine its application to large-scale organizational problems (such as policy systems) with more than three layers. Nevertheless, deeper investigation is required to properly demonstrate the applicability of *Net Pro* in real business environments, for instance by considering the way that users interrogate the tool, collaborate a decision, and suggest improvement opportunities.

5. Conclusions and opportunities

This paper presented a systematic procedure for making complex (interconnected) decisions and demonstrated its utility to the BT's field engineering system. Developed based on real constraints and data in the business and research gaps in academia, *Net Pro* offers a configurable and end-to-end systems modelling and analysis platform that can be applied to a variety of problems of realistic complexity with varying types of information and information of different quality. It can be constructed without programming, only based on the declarative knowledge of the components and their interdependencies, hence providing an alternative way of mining dependency data to general-purpose diagramming tools.

From a practitioners' viewpoint, *Net Pro* can enable analysts and decision-makers to understand where there are gaps in the system (e.g., a missing communication link), where effective interventions can be introduced, and what the potential unforeseen outcomes of a decision option are. Such knowledge can eventually help with 'increasing efficiency' which is a key consideration for managers, who want to ensure that their limited resources are most efficiently targeted in the areas where they can have the most positive direct and indirect influence. Notwithstanding that being compatible with the latest web-based technology can make a valid contribution to support socially distributed decision-makers.

From a research perspective, *Net Pro* is built upon the previous knowledge of the field and would be freely accessible to the research community to develop new systems modelling and analysis frameworks. The information about getting access to the software tool and using it would be available on the tool website: *http:www.virtualnetpro.com*. At the time of writing this paper, *Net Pro* is applying to the context of public health to assist policymakers in identification of (hidden) factors whose change play a key role in improving quality of life in the UK. Since the software tool is designed to be generic across disciplines, further development is under consideration to allow for more structured use of CP analysis methods in different settings. One possible direction for further development would be expanding the underlying DPM algorithm to encounter the directionality of influences, in terms of *positiveness* or *negativeness*. An additional extension would be expanding the program architecture to allow for modelling more than three layers, as well as improving the interoperability between *Net Pro* and other relevant decision support tools available in the business or across the research community.

CRediT authorship contribution statement

Mohammad Hassannezhad: Conceptualization, Methodology, Software, Formal analysis, Validation, Investigation, Visualization, Supervision, Writing - original draft, Writing - Review & Editing, Project administration. **Behzad Farahany**: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing - Original Draft, Visualization. **Fatemeh Barzegar**: Software, Formal analysis, Investigation, Data Curation, Visualization, Writing - original draft.

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